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CONTENT BASED IMAGE RETRIEVAL USING TEXTURE STRUCTURE HISTOGRAM AND COLOR

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ABSTRACT

Interests to accurately retrieve required images from databases of digital images are growing day by day. In this paper, a novel image feature descriptor, namely texture structure histogram (TSH) for content-based image retrieval is proposed. This method uses the color and edge orientation information to describe the image texture structure information. Considering the HSV color space conforms to humans' visual perception mechanism, the feature extraction is conducted in the HSV color space. This puts forward the non-equal interval quantization scheme that makes the expression of the image information to be more reasonable. Images are represented by certain features to facilitate accurate retrieval of the required images. These features include Texture, Color, Shape and Region. In feature representation phase, the feature fusion mechanism is used that made the color and shape information merge together and get a better result. The experiment results demonstrate that the proposed method is more efficient and have a high retrieval performance.

***Keywords:* Color, Feature Fusion, HSV Color Space, Image Retrieval, Texture Structure Histogram, Similarity Measures**

I INTRODUCTION

In recent years, with the rapid development of digital image processing technology, helping the user to find the multimedia information what they need quickly and effectively becomes a hot research topic at present. Image retrieval is a major component of multimedia information retrieval technology, and also one of the basic theory of video information retrieval, it play a significant role in the field of information retrieval. Image retrieval is based on users' query requests, extract an image or image set that related to the query image from the image dataset. Generally, three categories of methods for image retrieval are used: text-based, content-based and semantic-based [1]. The content-based image retrieval (CBIR) has been proposed in the early 1990’s [2]. This approach is to retrieve images using low-level features like color, texture and shape that can represent an image.

Color is a very important visual cue for image retrieval and object recognition. Color histograms are invariant to orientation and scale, and this feature makes it more powerful in image classification. Color histogram-based image retrieval is easy to implement and widely used in CBIR systems. Some of the commonly used color descriptors include compact color moments, the color coherence vector, and color correlo-gram [3].

Texture is one of the most important characteristics of an image. Texture features are also widely used in CBIR systems. Various algorithms have been designed for texture analysis, such as gray level co-occurrence matrices [4], the Tamura texture feature [5], the Markov random field model [6], Gabor filtering [7], and local binary patterns [8]. Tamura et al., based on human visual psychology research put forward some different methods to describe the texture feature, give a description of several different terms: coarseness contrast and directionality, line-likeness, regularity, roughness, etc.

In addition to color and texture features, shape feature is the most essential characteristics of depicting objects. But it is also most difficult to describe. The major difficulty is the segmentation of interested target. Currently commonly used to describe the shape of image retrieval methods mainly include two categories: based on edge and based on the shape of the area. The former using the edge information of images, while the latter using the area of gray level distribution information. Classical methods of describing shape features include the use of moment invariants, Fourier transforms coefficients, edge curvature and arc length [3,9].

This project uses the color and edge orientation feature that describe the texture information correctly. The rest of this describe the HSV color space and the color and edge orientation quantization scheme in the HSV color space. In section 3, we describe the feature extract and feature fusion.

II RELATED WORKS

Research on CBIR could be bifurcated into two groups on the basis of the features used to retrieve the required image. Early approaches used a single feature out of the available features namely shape, texture, color and region for retrieval of the required image. Results of single feature based retrieval systems were not satisfactory because generally image contains several visual features.

The shape descriptor also provides dominant information in image retrieval because shape is the only source through which humans can recognize objects. The shape feature can be retrieved by two methods boundary based shape feature extraction and region based shape extraction.

An efficient CBIR system with better performance is presented by using the wavelets decomposition of image; they have generated the composite sub-band gradient and the energy distribution pattern string from the sub images of are generated by means of wavelet decomposition to the input image . For filtering out the undesired images a technique based on energy distribution pattern strings fuzzy matching is used.

Texture has no formal definition but intuitively it provides measure of properties such as coarseness, regularity and smoothness. It plays a role in human visual perception and interpretation. Texture describes in three approaches, namely, structural, statistical and spectral. In structural approach the texture is formed of small texture elements called 'texels' by following placement rules. The statistical method assumes texture by means of statistical grey level features of image pixels. The spectral approach is based on filtering theory in frequency domain and power density function. The structural approach is not so prevalent because majority of the natural structures contain asymmetrical shapes.

III PROPOSED SYSTEM

It is proposed to implement "Content –Based Image Retrieval" using different features like Color, Texture, Shape and, Objects and their relationships. The proposed system will produce the output as images which are relevant to the query Image. The proposed system flowchart is as shown in Fig. 1.

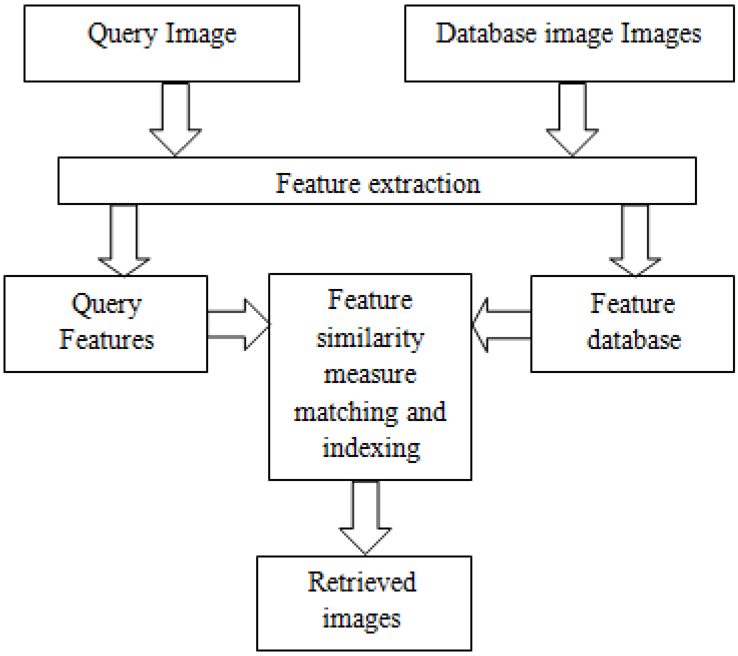

Fig.1. Proposed System Flowchart

3.1 Retrieval Based on Colour

Several methods for retrieving images on the basis of colour similarity are being used. Each image added to the database is analyzed and a colour histogram is computed which shows the proportion of pixels of each colour within the image. Then this colour histogram for each image is stored in the database. During the search time, the user can either specify the desired proportion of each colour (75% olive green and 25% red, for example), or submit a reference image from which a colour histogram is calculated.

3.2 Retrieval Based on Structure

The ability to match on texture similarity can often be useful in distinguishing between areas of images with similar colour. A variety of techniques has been used for measuring texture similarity in which the best established rely on comparing values of what are known as second order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness. Alternative methods of texture analysis for retrieval include the use of Gabor filters and fractals. Texture queries can be formulated in a similar manner to colour queries, by selecting examples of desired textures from a palette, or by supplying an example query image. A recent extension of the technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived code words representing important classes of texture within the collection.

3.3 Retrieval Based on Shape

The ability to retrieve by shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept and there is considerable evidence that natural objects are primarily recognized by their shape. A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query.

IV HSV COLOR MODEL

HSV colour model stands for Hue Saturation Value colour model. This model describes colours in terms of their shades and brightness (Luminance) and offers a more intuitive representation of relationship between colours. Basically a colour model is the specification of coordinate system and a subspace within that, where each colour is represented in single point.

Hue represents the dominant wavelength in light. It is the term for the pure spectrum colours. Hue is expressed from 0º to 360º. It represents hues of red (starts at 0º), yellow (starts at 60º), green (starts at 120º), cyan (starts at 180º), blue (starts at 240º) and magenta (starts at 300º). Eventually all hues can be mixed from three basic hues known as primaries.

Saturation represents the dominance of hue in colour. It can also be thought as the intensity of the colour. It is defined as the degree of purity of colour. A highly saturated colour is vivid, whereas a low saturated colour is muted. When there is no saturation in the image, then the image is said to be a grey image.

It describes the brightness or intensity of the colour. In other words value is defined as a relative lightness or darkness of colour.

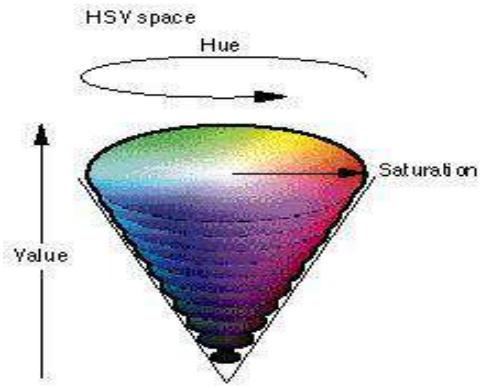

Fig.2. HSV Color Model

4.1 HSV Color Space and Quantization

Color information is the bottom and intuitive physical characteristics. Because color is robust to the effects of noise, size and orientation of image, so color feature is most commonly used in content-based image retrieval. Color quantization is closely related to the color space. Many kinds of color spaces have been proposed and used for image retrieval. However, different color space has different application, we usually hard to decide which kind of color space is most suitable for our image retrieval algorithm. The HSV color space could mimic human color perception well [12].

4.1.1 Color Non-Equal Interval Quantization in HSV Color Space

In order to cut down the computing complexity and extract the color features in efficient way, we use HSV color space and quantize it into non-equal interval 72 bins, thus we get the color index image *C(x, y)*. As is known to all, quantizing the *H*, *S* and *V* channels uniformly is not suitable for human's visual perception and recognition.

(a) (b) (c)

Fig.3. HSV quantization scheme: (a) RGB Image (b) Equal Interval Quantization (c) Non-Equal Interval Quantization

4.1.2 Edge Orientation Quantization in HSV Color Space

Edge orientation also plays an important role in content-based image retrieval. Edge orientation information can represent the object's shape and boundaries perfectly. In this paper, we use a simple and effective method for edge orientation detection.

Let $a = (Hx, Sx, Vx)$ and $b = (Hy, Sy, Vy)$, where *Hx, Sx* and *Vx* denotes the gradient in *H*, *S* and *V* channel along horizontal direction respectively, and *Hy, Sy* and *Vy* denotes the gradient in *H, S* and *V* channel along vertical direction respectively. Here we use the Sobel operator. After the edge orientation of each pixel has been computed, the orientations are uniformly quantized into 18 bins with each corresponding to angle of 20°. It is most reasonable according to the experiments. Thus we get the edge orientation index image.

4.2 Feature Extraction

4.2.1 Structure Map Construction and Feature Representation

According to the color index image, we build the color structure map. Similarly, we can build the edge orientation structure map and we omit it here. The details of the process are illustrated in Fig.4. For the color index image, a 3×3 block filter throughout the image from left to right and top to bottom with 3-step length. Then, we consider the value of central point of the 3×3 block and the values of its four neighbourhoods. If the

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value of central point equals to that of its four neighbourhoods, then the values of the 3×3 block will be remained, otherwise, the values will be set to zero. Finally, we get the color structure map *T*(*x*, *y*). Similarly, the edge orientation structure map *O*(*x*, *y*). Fig.5 shows the processing of the color information detection. After previous operation, we can obtain the color structure map *T*(*x*, *y*) and its index value.

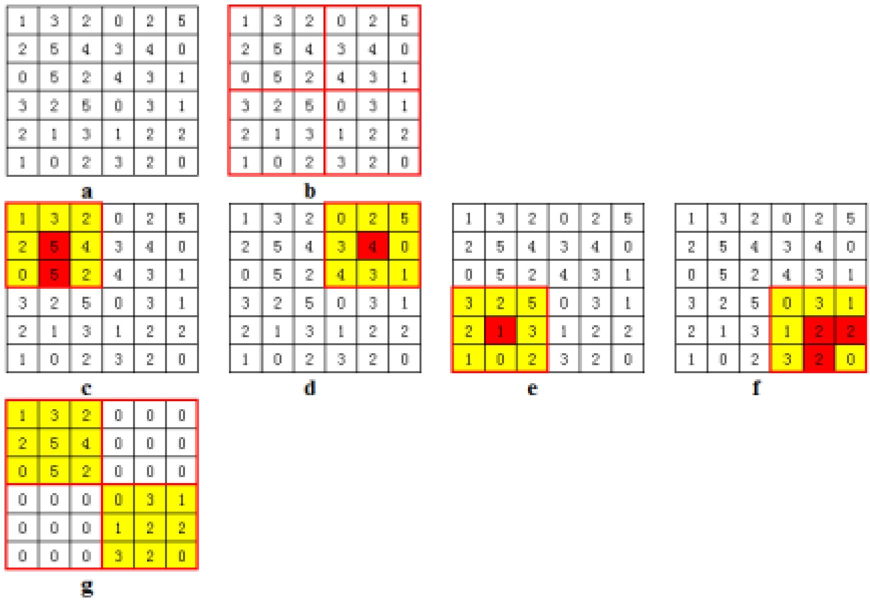

Fig.4.The Process of Color Structure Map Constructing

4.3 Feature Fusion

For some images, its texture information is very rich. However, for some kinds of images, its edge orientation information seems to be much richer. Thus we give different weights to the two features according to the attribute of images. According to the experiment, we train the parameters to get the most suitable one whose precision is the highest. We combine *Hcolor* (*T* (*x*, *y*)) and *Hori* (*O*(*x*, *y*)) as the final feature vector *H*, namely, texture structure histogram (TSH, for short) [12].

V SIMILARITY MEASURES

The retrieval process is performed by different similarity measuring techniques. The result of the query may not be a single image. It is a series of images categorized by the similarity of retrieved image with the query image. Similarity measures are used to find the correspondence of the query image with the image stored in the database.

An image may contain visual information or semantic information. The visual information can be represented in form of shape, color, texture and spatial relations. The extracted visual features are considered as feature vector that are kept in feature database. Retrieval performance of the CBIR systems is affected by similarity measures. Here I denote the query image, J is the image in database, fi (I) represents the number of pixels in i^{th} bin of query image [13].

5.1 Minkowski-Form Distance

The Minkowski-form distance La is apt for the computation of distance between two images when each of the image feature vectors having equal importance and are independent from each other. It is defined as:

$$D(I,J) = \sqrt{\sum_{i=1} |f(i) - f(i)|^{a}} \qquad (1)$$

5.2 Mahalanobis Distance

Another metric suitable for all dimensions of image feature vector is defined as:

$$D(I,J) = \sqrt{(FI - FJ)^{T} C(-1)(FIFJ)} \qquad (2)$$

5.3 Cosine Similarity

Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them. The cosine of 0° is 1, and it is less than 1 for any other angle. It is thus a judgment of orientation and not magnitude: two vectors with the same orientation have a cosine similarity of 1, two vectors at 90° have a similarity of 0, and two vectors diametrically opposed have a similarity of -1, independent of their magnitude. Cosine similarity is particularly used in positive space, where the outcome is neatly bounded in [0, 1]. The equation is given by:

$$\cos\theta = \frac{\vec{a}.\vec{b}}{\|\vec{a}\|\|\vec{b}\|} \qquad (3)$$

VI MODULE DESCRIPTION

The system is implemented using MATLAB. Following are the modules used in the system:

1) RGB Projection: The **RGB color model** is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as conventional photography.
In this module the RGB Projections is used to find the size of the image vertically and horizontally.

2) Image Utility: Whenever minimizing the error of classification is interesting for CBIR, this criterion does not completely reflect the user satisfaction. Other utility criteria closer to this, such as precision, should provide more efficient selections.

3) Comparable Image: In this module a reselection technique to speed up the selection process, which leads to a computational complexity negligible compared to the size of the database for the whole active learning process. All these components are integrated in our retrieval system, called RETIN and the user gives new labels for

images, and they are compared to the current classification. If the user mostly gives relevant labels, the system should propose new images for labelling around a higher rank to get more irrelevant labels.

4) Similarity Image: The results in terms of mean average precision according to the training set size (we omit the KFD which gives results very close to inductive SVMs) for both ANN and Corel databases. One can see that the classification-based methods give the best results, showing the power of statistical methods over geometrical approaches, like the one reported here (similarity refinement method).

5) Result: Finally, the image will take the relevant image what the user search. One can see that we have selected concepts of different levels of complexities. The performances go from few percentages of Mean average precision to 89%. The concepts that are the most difficult to retrieve are very small and/or have a much diversified visual content. The method which aims at minimizing the error of generalization is the less efficient active learning method. The most efficient method is the precision- oriented method.

VII EXPERIMENTAL RESULTS

Fig.5. Similar Images of Query Image Retrieved

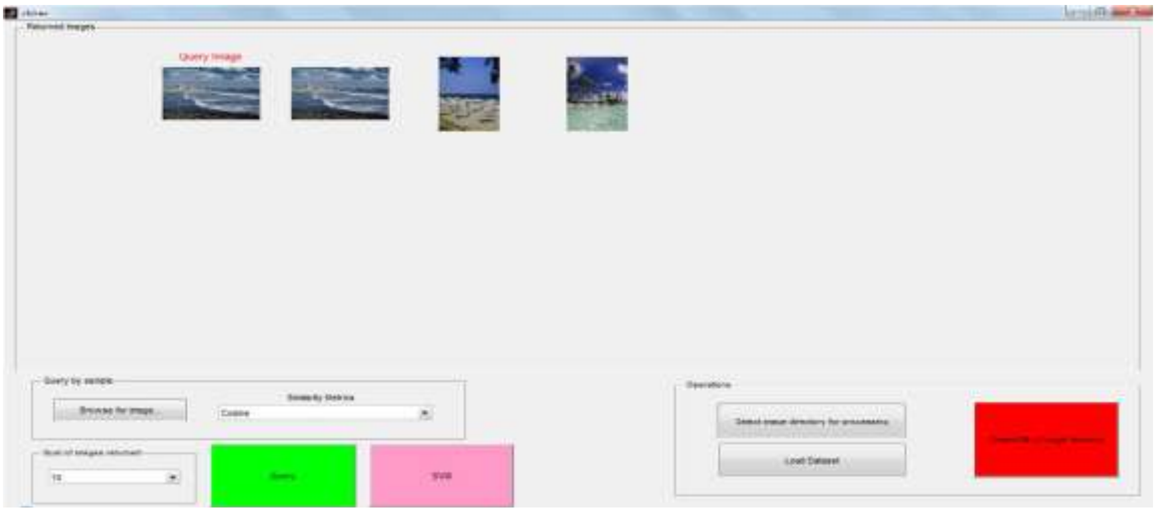

Fig.6. Selection of Distance Metrics

VIII APPLICATIONS AND CONCLUSION

CBIR finds application in art collections, medical image databases, scientific databases, textile industry etc. Texture Structure Histogram (TSH) is a novel image feature representation method. The non-equal interval quantization scheme of HSV color space is used, because HSV color space conforms to people's subjective judgment of color similarity.TSH integrates the advantages of both color and texture features, and shows a good retrieval performance.

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